# Data-driven Pricing and Control for Low Carbon V2G Charging Station with Balancing Services.

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***Abstract*—The transition to a low carbon transportation system has brought many challenges for researchers, one major challenge is how to ensure power system reliability as a result of high load demands to supply energy to Electric Vehicles (EVs) while coping with increasing distributed and renewable sources of energy. Consequently, energy management strategies have become very important in the future smart grid design. An aggregator could play a critical role when integrating management strategies between EVs and the grid, based on emerging market opportunities and different variables from the stakeholders involved such as EV requirements, balancing services and profitability of the Charging Station (CS). This paper proposes a data-driven optimisation algorithm with pricing and control modules that communicate with each other to achieve a successful integration with the grid by charging at the right price and at the right time. The results show customers can be positively engaged with pricing signals while providing support to the power system. In conclusion, this paper can be used as a foundation to a commercial CS that may enhance an effective integration of EVs with the grid.**

## I. Introduction

Increasing penetration of renewable energy sources and a near zero carbon transport sector are challenging the reliability and resilience of today´s electricity network [1]. Consequently, the system operator of Great Britain, National Grid (NG) reports that ancillary services will play a critical role for energy transition. Therefore, innovative technologies and new business models are required to provide solutions considering energy management strategies along with emerging electricity markets [2]. A recent report of Vehicle to Grid (V2G) projects in Europe shows it's possible to use V2G technology to deliver value to customers [3]. However, the collaboration between a Charging Station (CS) provider (Enel X), V2G vehicle providers (Nissan, Mitsubishi, PSA Groupe) and an energy aggregator (Nuvve) [4], is the only project identified at commercialisation stage . As a result, there are still challenges to integrate V2G users with global energy markets.

Sortomme *et al.* [5] proposed an energy bidding strategy of an energy aggregator that models Electric Vehicle (EV) charging and discharging while providing frequency regulation and spinning reserves services to the grid. Vagropoulos *et al.* [6] also proposed a bidding strategy with charging only. They considered additional penalties to customers and to the energy aggregator, in case of energy variations from the day ahead. Likewise, van der Linden *et al.* [7] showed a bidding strategy and control over bid pricing that works when the energy price is lower than the market capacity clearing price. Chen *et al.* [8] proposed an energy management system with V2G capability and a photovoltaic (PV) CS where EVs are classified in rigid and flexible loads to support ancillary services. These authors didn't provide incentives for customers to engage them in the market. So, it is hard to tell customer willingness to participate with energy management systems.

Demand response strategies are a promising tool for enabling renewables [9]–[11] because price mechanisms can be used to influence customer behaviours according to energy markets [12], [13]. Rigas *et al.* [14] used price congestion signals as promoters for allocating different energy time slots in a CS. This balance was created under the assumption that EVs look for cheaper prices. Yoon *et al.* [15] proposed a stackelberg based model where customers respond to price signals until reaching an equilibrium point between customer and retailer for home charging. The availability of information of the grid can also be used to provide accurate supply and demand curve responses using data association mining as proposed by Zhou *et al.* [16]. This data can also be used to calculate demand elasticity and price tariffs like: time of use, as modeled by Galvis and Costa [17] and Wang *et al.* [18] or dynamic pricing as proposed by Ferreira and Dortolina [19], and Hu and Li [20].

The added value in this paper relies mainly on research focus in economical operation of a solar V2G CS which is one of the hardest key factors to commercialisation of this technology as discussed in [3]. Even though it is a very important research topic, there are limited multidisciplinary publications in this area. This paper proposes usage of microeconomic theory in pricing schemes to manipulate energy charging of customers in specific time periods depending on customer's response to price. Then, a second level optimisation is integrated to control the charging of EVs with different technology and customer settings. Thereby, the contributions of this paper are outlined below:

1) New demand response pricing scheme is proposed by using inverse demand curve and optimal pricing to adjust demand for providing balancing services.
2) Energy bidding planning algorithm is proposed using

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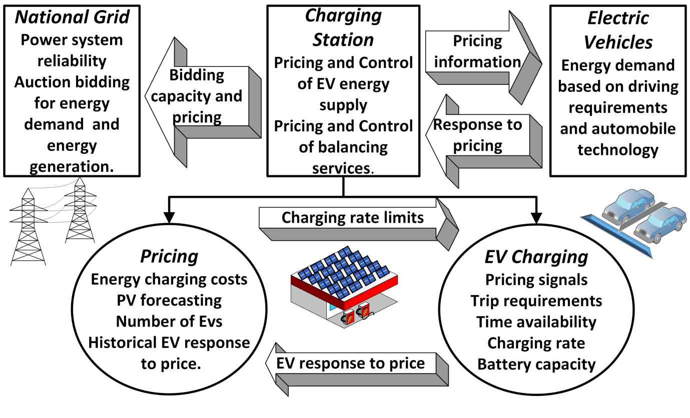


Fig. 1. Proposed model with activities and communication between stakeholders involved and variable inputs for the pricing and EV charging modules.

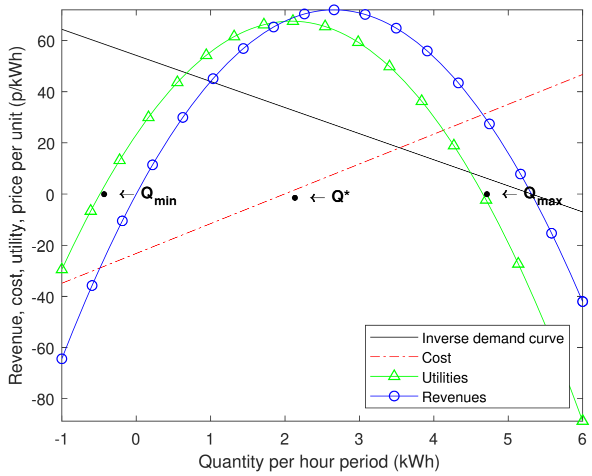


Fig. 2. Mathematical relationship of variables in pricing module.

revenues and costs of the CS which translates into a profitable pricing and control operation in a solar CS.

3) Integral bi-level optimisation and two-way communication system that can reinforce the behaviour of the CS is proposed.
4) Adaptive model is studied that is compliant with secondary frequency regulation market in the United Kingdom which can be used by researchers and industrial research and development.

## II. Proposed Algorithm

The business model of the CS proposed in this paper is applicable for big parking lots such as the ones in office buildings or supermarkets. The revenues come from charging of EVs and from participating in balancing grid services. The three stakeholders involved are NG, the CS and EV customers. Fig. 1, illustrates the main activities of each stakeholder and key variable inputs needed for the CS operation. The CS operates with a bi-level optimisation where the CS first computes economical pricing schemes that are then followed by EV charging strategies. Both computations are important for the CS and EV drivers respectively, the pricing schemes in the pricing module ensure a financially sustainable operation of the CS and the EV charging module ensures customers save money as much as possible while complying with technology and customer restrictions. Consequently, the CS is the price maker (monopoly case is assumed) that considers solar generation capacity, number of EVs in the CS, energy price to buy from the grid when necessary and demand response to charging prices when setting pricing schemes. The EV charging module processes the charging strategies assuming customers will respond to price signals by charging when energy is cheaper and as long as restrictions like charging availability, driving requirements, charging and battery limits are met. These two modules in the bi-level optimisation are explained in more detail in the following paragraphs.

### A. Pricing module

The pricing algorithm is obtained from two sources: an optimum pricing and a demand response pricing, commonly referred as a cost and customer based pricing respectively [21]. This module computes day ahead pricing schemes divided in 24 hour periods. A linear regression estimates responsiveness of EV customers to price as a first step in the pricing module. Details of the real data used for the model are discussed in section III.

$$P = 54.201 - 20.405 \cdot Q \tag{1}$$

The linear regression or inverse demand curve includes price ($P$) in pounds, as the dependent variable and quantity of customer demand ($Q$) in kWh, as the independent variable. Thereby, a linear fitting model is used to estimate the coefficients of the intercept and the coefficient of demand. The results of the linear fitting are in equation (1).

$$R = P \cdot Q \tag{2}$$

$$C = C_G \cdot (Q - P_{PV}) \tag{3}$$

To calculate the optimum price that maximises utilities, the next step is to calculate revenues ($R$) and costs ($C$). Equation (2) represents the revenues obtained by multiplying price times quantity. Costs of the CS in (3) are based on an approximation of cost times quantity of energy to buy from the grid minus the cost of PV generation which is considered to be zero. Therefore, costs are obtained when subtracting the onsite PV generation quantity available per each EV ($P_{PV}$) from the quantity demanded per EV times the grid energy cost ($C_G$).

$$MR = P \cdot \frac{\partial Q}{\partial Q} + Q \cdot \frac{\partial P}{\partial Q} \tag{4}$$

$$MC = C_G \cdot (Q - P_{PV}) \cdot \frac{\partial}{\partial Q} \tag{5}$$

$$MR - MC = 0 \tag{6}$$

Revenues and costs are differentiated to obtain a marginal revenue (MR) and marginal cost (MC). Then these are equalized to find the optimum quantity that can produce maximum utilities (4-6). The optimum quantity (Q*), is calculated when solving equation (6) for $Q$, this specific procedure is common in microecomomic theory (utility maximisation of the monopoly case) [22]. This calculation will be the reference to either sum or to subtract the corresponding bidding quantity to increase or decrease energy in a balancing service. To illustrate the model, Fig. 2 shows the quantity (demand of EVs) and its relation to costs, utilities and revenues calculated from the inverse demand curve.

$$R - C = 0 \tag{7}$$
$$+Qbid \leq Q_{max} - Q* \tag{8}$$
$$-Qbid \leq Q * - Q_{min} \tag{9}$$
$$P_{DR} = 54.201 - 20.405 \cdot (Q * \pm Qbid) \tag{10}$$

The next step is to calculate the expected price that will keep the right charging quantity depending on the corresponding contracted energy capacity with the grid. It is important to take into account a maximum and minimum quantity ($Q_{max}$, $Q_{min}$) to either increase or decrease energy of EVs because the price and quantity relationship can provoke negative utilities for the CS if not managed appropriately. Thus, these bid quantities are calculated from (7), assuming there aren't any utilities obtained from buying or selling electricity to EVs, the utilities are instead obtained from balancing services offered to the grid. These maximum and minimum quantities limit the bid to provide balancing services when controlling an energy increase bid ($+Qbid$) in (8) and an energy decrease bid ($-Qbid$) in (9). Finally the pricing values: optimum price and a demand response price ($P_{DR}$), are calculated from (1) and (10) to be concatenated in a final price matrix. Here the optimum price is used for the time periods where there isn't need for balancing services and the maximum and minimum prices are used when balancing services are required during the day.

$$U = R - C \tag{11}$$
$$P_{NG} = ((U * - U_{bid})/(Q * - Q_{bid})) \cdot (1 + u) \tag{12}$$

After getting the prices for selling (charging) and buying energy from EV users (discharging) when applicable, it is also important to set the prices of the balancing services to enter in NG auctions. These NG prices should produce additional revenues to the normal operation of the CS. Therefore, equation (11) calculates the utilities ($U$) with data from the previously mentioned quantities and prices obtained from (6), (7), and (1), (10) respectively. These are used in (12) to obtain an optimum utility ($U*$) and a utility when providing balancing services ($U_{bid}$) to then calculate the price to enter NG balancing services of increase and decrease of energy ($P_{NG}$) with an expected margin of utility (u) that is specified by the CS.

### B. EV charging module

To integrate the pricing model with a robust EV charging algorithm, the second level in our optimisation problem is based in charging control from [5] with some omissions and additions of constraints that include relevant variables such as EV customer charging requirements, charging limits from the solar CS and EV battery limits. The complete optimisation problem is formulated below:

$$\underset{Q(t)}{\text{Minimise}}\ C_{EV} = \sum_{t=1}^{T} P(t) \cdot Q(t) \tag{13}$$

Where,

$$SOC(t) = SOCI(t-1) + Q(t) \tag{14}$$
$$Min(t) = min(Q_{EV}, Q_{CS}, Q_{max}) \tag{15}$$
$$Max(t) = max(-Q_{EV}, -Q_{CS}, Q_{min}) \tag{16}$$

Subject to

$$Trip = SOC_F(t) - SOC_I(t) \tag{17}$$
$$0.01 \cdot B \leq SOC(t) \leq B \tag{18}$$
$$Q(t) \leq Min(t) \cdot AV(t) \tag{19}$$
$$Q(t) \geq Max(t) \cdot AV(t) \tag{20}$$

$$Q(t) \in \mathbb{R}$$

The objective function considers the minimisation of customer costs ($C_{EV}$) when charging in (13). The charging rate is the decision variable which will be expected to follow pricing signals from the pricing module, however there aren't restrictions to charge when EVs are not able to follow price signals because of time or trip restrictions. That is to say, customers can have the option to pay more if required. The model considers the dynamics of state of charge of the EV ($SOC$) with an initial state of charge ($SOC_I$) and charging rate during the available charging period in (14). The quantity to charge an EV is restricted to a minimum ($Min$) and a maximum ($Max$) possible charging rate when taking into account the charging rate limit of the EV ($Q_{EV}$), CS charging rate limit ($Q_{CS}$) and economic rates obtained from the pricing module ($Q_{max}$, $Q_{min}$) as formulated in (15,16). The restrictions of the EV charging module start with the trip requirements of individual EVs ($Trip$) that are calculated from the difference in a final ($SOC_F$) and initial state of charge in (17). The charging rate complies with charging rate limits defined in (15) and (16) and are formulated in (19, 20) with an addition to EVs' time availability for charging during a day ($AV$). The optimisation also considers a limit in the negativity of the decision variable $Q(t)$ when discharging is not necessary, however it can become negative when discharging is economically possible for the CS.

## III. Simulation

The bi-level optimisation is solved in MATLAB, the EV charging module uses Yalmip toolbox [23] and Gurobi [24] for formulating and solving matters. The algorithm is tested using a basic case scenario and different inputs of variables to perform several sensitivity analysis and charging profile comparisons.

The pricing basic case scenario uses real world quantity and price response data from trial 3 of Electric Nation Project kindly provided by EA Technology [25]. Monthly values (October to

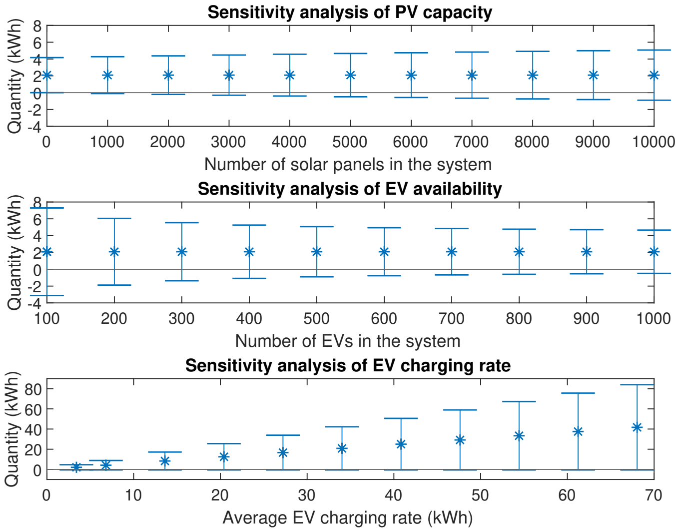


Fig. 3. Sensitivity analysis of data-driven estimation of bids for balancing services provided by each EV.

December) of price (pence per kWh) and demand are aggregated to create a better estimation of an expected inverse demand curve with a total of 40 observations, an adjusted R-squared value of 0.815 and a p value close to zero that shows statistical significance of the model. Fixed variables in the basic case scenario are: 24 hours in a day, 1000 EVs in the charging station, cost of energy (to buy from the grid) is 11.66 p/kWh, number of PV panels in the system is 5000, data forecasting of power capacity for each PV panel was obtained from [26] considering an average AC output in a year divided by the number of EVs, timings for balancing services to either decrease or increase energy are from 10:00 to 11:00 hrs and from 14:00 to 15:00 hrs respectively. The sensitivity analysis for the pricing module contains all variables of the basic scenario except for a variation of number of PV panels in the system from 0 to 10000, number of EVs in the system from 100 to 1000.

The three charging profile comparisons for the EV charging module use a basic case scenario with specifications of the Nissan Leaf which is compared with the Tesla model X in Fig. 4, both specifications are obtained from [27]. The battery capacities and charging rates for the Nissan Leaf and the Tesla model X are 40 kWh, 6.6 kWh and 100 kWh, 16.5 kW respectively. Both EVs had initial state of charge of 20% of the total battery capacity and 100% time availability to charge from 8:00 to 18:00 hrs. The EV charging rate of the inverse demand curve data was increased in quantity to allow a difference in charging rate for the system (calculated from the pricing module) from 2 to 20 times the original charging rate, the minimum and maximum rate restrictions of the model were also updated to reflect these changes in equations (15) and (16). The charging profile comparison with non technical requirements uses also the EV charging basic case scenario and it's compared with trip requirements of 27 kWh and time availability to charge from 10:00 to 14:00 hrs. The final charging profile comparison

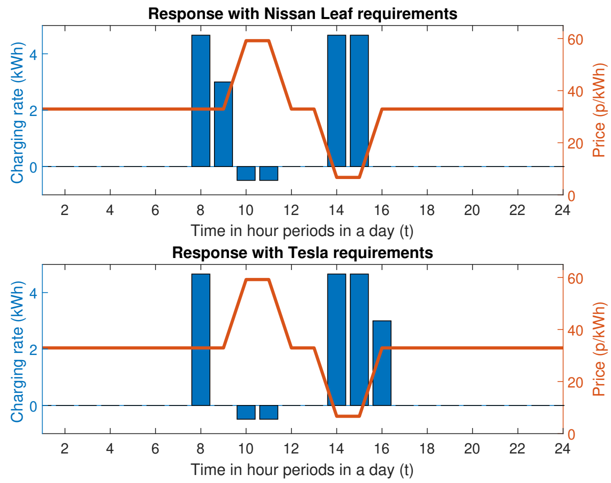


Fig. 4. Analysis of data-driven demand response with two cases of EV technology requirements (different charging rate and battery capacity).

is performed to compare EV response to price considering the pricing module's basic case scenario against a fixed price of 31 p/kWh.

## IV. Results

The proposed algorithm is analyzed in this section with different input parameters. The testing starts with a sensitivity analysis of the pricing module to show the adaptability of the model and its capacity to estimate energy bids for balancing services with different sizing of the PV system, number of EVs in the CS and charging rate capabilities of both CS and EVs. Moving on with the testing, the EV charging module is evaluated against different responses of EV drivers with two different car capabilities (charging rate and battery capacity included). Another test compares two customers with different driving requirements (trip and available time for charging included). A final test is executed against having and not having the price scheme as an incentive mechanism to influence customers to provide balancing services.

### A. Pricing module

Fig. 3 shows the quantities or capacity offers in kWh that the CS is able to provide for balancing services: the asterisk represents $Q*$, the top and bottom lines in the error bar represent the $Q_{max}$ and $Q_{min}$ respectively. The basic case scenario outlined in the simulation section is used as a basis to increase the number of PV panels. The graph at the top shows that an increase in size of the CS reduces the costs which allows the CS to increase its capability to provide a greater bid capacity per each EV from 4.17 kWh to 5.069 kWh usable for energy increase and from -0.660 to -0.898 usable for energy reduction. This difference in quantity becomes significant when multiplied by the total quantity of EVs in the system (1000 EVs) as there is extra capacity for balancing services.

To continue with the results of Fig. 3, the graph in the middle shows the behavior of the bid capacity when increasing the

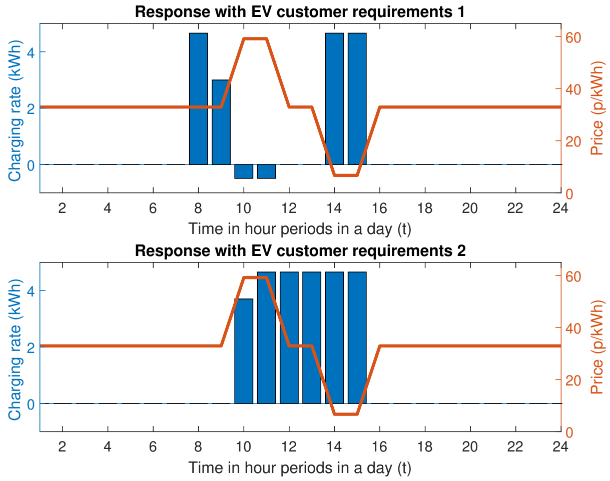


Fig. 5. Analysis of data-driven demand response with two cases of EV customer requirements (different trip and available time for charging).

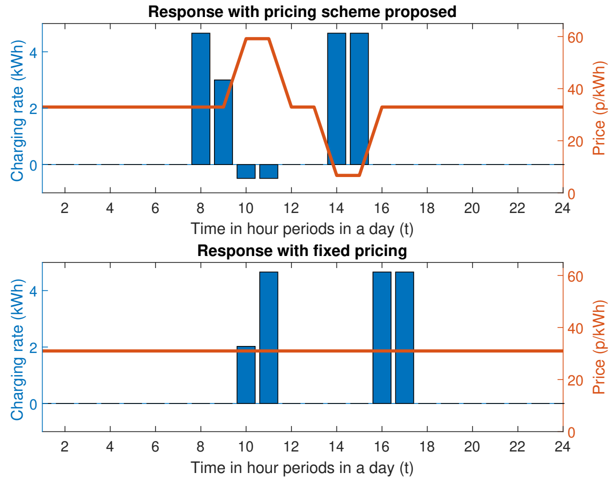


Fig. 6. Analysis of data-driven demand response with pricing scheme and without pricing changes.

number of vehicles in the system. We can observe that this case scenario contrasts with the graph at the top: the individual bid does not increase, it actually reduces from 7.292 kWh 4.659 kWh usable for energy increase and -0.672 kWh to -0.489 kWh usable for energy reduction. This decrease in EV individual energy bid capacity can be attributed to an increase of costs to supply energy to EVs as the PV system may not be able to cope with increasing energy demand and grid energy is relatively expensive compared to onsite generation (PV generation cost is assumed to be zero). However, as the number of EVs increases, the total bid capacity increases from 0.729 MWh to 4.659 MWh and from -0.067 MWh to -0.489 MWh for energy increase and energy decrease. Therefore, having an increasing number of EVs in the system is beneficial for total capacity bidding.

To finalize with the testing of the pricing module, the graph at the bottom of Fig. 3 examines the basic scenario with an increase of potential charging rate from both the CS and EVs. The bid capacity increases as the charging rate rises. However, the increasing changes are not the same for for energy increase in contrast with energy decrease. The reason for this difference can be attributed to the price and quantity response reference used in the model which can be preventing the negative charging rate to keep increasing at the same rate of the positive charging rate. In other words, with the current inverse demand curve in the model it is too expensive to increase the negative charging rate as it represents a high cost for the CS. In total, the capacity for bidding is from 4.659 MWh to 83.951 MWh and from -0.489 MWh to -0.542 MWh available for balancing services.

### B. EV charging module

The charging module integrates with the pricing module as it models the demand response to price signals. Fig. 4 evaluates the response of EVs considering the charging rate and battery capacity of a Tesla model X against the basic case scenario of the pricing and EV charging module. Both automobiles behave similarly, this can be explained by the restrictions of the model as the $Q_{max}$ and $Q_{min}$ are 4.659 kWh for energy increase and -0.489 kWh for energy decrease per EV, this is less than the maximum rate limits of the EVs and the CS. Both automobiles take advantage of the low prices for energy increase from 14:00 to 15:00 hrs and support the grid with V2G capability from 10:00 to 11:00 hrs as they take advantage of the high prices to sell energy to the CS while the CS uses it to balance the grid.

Fig. 5 shows variation in the response of EVs when the requirements for driving (Trip) and available time for charging are affected. The graph at the top shows a flexible customer 1 with lower energy demand and more available time for charging compared to customer 2. The response of customer 1 works pretty well as it follows price signals. Customer 2 is a relative extreme case where the demand for energy is quite high and there is less available charging time at the CS. Unfortunately, this prevents customer 2 from providing V2G during energy decrease periods from 10:00 to 11:00 hrs. Although, the charging rate during energy increase can still be useful for the CS as this can be aggregated to increase demand at the CS for grid balancing purposes.

To finish the testing of the EV charging module, the optimisation is evaluated with a fixed pricing as in [5] and with the price scheme proposed. The graph at the bottom of Fig. 6 shows an almost random charge rate at any hour during available charging time because without proper pricing signals to customers, there isn't an influence to charging behavior. In this case the minimum cost to charge the EV means charging at any time as long as trip requirements are satisfied. The response with the pricing scheme shows effective influence over EV charging when evaluating the pricing and EV charging basic case scenario.

## V. Conclusion and Future Work

This paper presents a bi-level optimisation algorithm for the creation of pricing schemes and EV charging control that together control the operations of a solar CS to satisfy EV requirements while providing balancing services to the grid. Firstly, a pricing algorithm models the quantity of energy consumption with price depending on a total allowed pricing tariff to increase or decrease energy up to a specified profitable bid allowance. Secondly, a control algorithm is presented to optimise the charge of EVs considering energy savings for customers and restrictions of the customer and the CS. The pricing module demonstrated a robust structure to estimate a profitable and demand responsive pricing scheme. The control module effectively provided a demand response to adjust charging rate with pricing mechanisms.

Future research directions of the model proposed in this paper could be extensions to other pricing considerations such as competition with other CS', discount coupons and real time pricing. The business model of the CS includes balancing services to NG, balancing support could also be extended in the distribution system operation level or could be merged with other energy trading mechanisms. Other potential research gaps of the model include analysis of statistically significant results with addition of stochastic variables such as arrivals, departures, weather forecasting, initial SOC and estimation of updated inverse demand response curve in time. In addition, it is possible to incorporate initial investment and operational cost values for sizing and location for CS planning purposes. Finally, a coordinated and real time charging control that can cope with different charging technology and uncertainty of customer requirements would be ideal.

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